Lecture note – Introduction to prediction and something about the iid model

First about prediction. The iid model will be discussed in example 4 below.

When we want to estimate the future outcome (observation) of a random variable, $X$, we use the term prediction instead of “estimation”. In contrast, the term estimation is reserved for the task of estimating a fixed unknown quantity (parameter) in a population. In the special case when $X$ represents a future value in a time series, we usually instead use the term, forecasting (Norwegian: prognose), for prediction.

1 Case 1 – Prediction of $X$ when the distribution of $X$ is known

Suppose that $X \sim f(x)$ (pmf or pdf) where $f$ is known. We want to predict (guess) the outcome, $X_{obs}$, of a future observation of $X$ – an outcome that is not yet known. Let $c$ denote our prediction (guess).

What is the best way to choose $c$?

The answer to this question does not have a universally valid solution, but will depend on the criterion of “best” that we use. Such a criterion is usually formulated in terms of the average value of a suitable loss function. The following three criteria (especially crit.1) are among the most common:

**Criterion 1** Loss function \( L_1(c) = (X - c)^2 \) (prediction error)\(^2\).

Choose $c$ to minimize expected loss \( E[(X - c)^2] \) (also called “the mean squared error” or MSE):

**Answer:** Best prediction is the expectation, \( c = \mu = E(X). \)

**Criterion 2** Loss function \( L_2(c) = |X - c| \) = |prediction error|.

Choose $c$ to minimize expected loss \( E|X - c| \).

**Answer:** Best prediction is \( c = m = \text{median}(X). \)

**Criterion 3** (Mostly used for discrete distributions).

Loss function, \( L_3(c) = \begin{cases} 0 & \text{if } c = X_{obs} \\ 1 & \text{if } c \neq X_{obs} \end{cases} \)

Choose $c$ to minimize expected loss = \( E(L_3(c)) = 0 \cdot P(X = c) + 1 \cdot P(X \neq c) = 1 - P(X = c) \)

**Answer:** Best prediction is $c$ = the most likely observation = the $c$ that makes $P(X = c)$ largest
(also called the mode in the distribution of $X$).
Example of criterion 3: Suppose the pmf of $X$ is given by

<table>
<thead>
<tr>
<th>$x$</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f(x)$</td>
<td>0.5</td>
<td>0.3</td>
<td>0.2</td>
</tr>
</tbody>
</table>

The best guess (prediction) of $X$, according to crit. 3, is $c = 1$. This way to predict is probably the common way applied intuitively by most people (being risk averters…).

Proof of criterion 1. We have (using that $\mu - c$ is a constant):

$\text{MSE} = E(L_1(c)) = E[(X-c)^2] = E[(X-\mu + \mu - c)^2] =

(1) \quad E[(X-\mu)^2] + 2(\mu-c)E(X-\mu) + (\mu-c)^2 = E[(X-\mu)^2] + (\mu-c)^2 =

= \text{var}(X) + (\mu-c)^2$

which shows that minimum MSE is obtained by choosing $c = \mu$. (End of proof).

Proof of criterion 2. The proof in the discrete case is a little tricky - so we skip that and assume that $X$ is a continuous rv with pdf, $f(x)$ and cdf $F(x)$. Then

$E[L_2(c)] = E|X-c| = \int_{-\infty}^{\infty} |x-c| f(x) dx = \int_{-\infty}^{c} (c-x) f(x) dx + \int_{c}^{\infty} (x-c) f(x) dx$

$= \int_{-\infty}^{c} (c-x) f(x) dx + \int_{c}^{\infty} (x-c) f(x) dx = c \int_{-\infty}^{c} f(x) dx - c \int_{-\infty}^{c} f(x) dx + \int_{c}^{\infty} x f(x) dx + \int_{c}^{\infty} x f(x) dx$

$= cP(X \leq c) - cP(X > c) - \int_{-\infty}^{c} x f(x) dx + \int_{c}^{\infty} x f(x) dx$

$= c \left[ 2F(c) - 1 \right] - \int_{-\infty}^{c} x f(x) dx + \int_{c}^{\infty} x f(x) dx$

Using that $\frac{d}{dc} \int_{-\infty}^{c} x f(x) dx = cf(c)$ and $\frac{d}{dc} \int_{c}^{\infty} x f(x) dx = -cf(c)$, we get

$\frac{d}{dc} E[L_2(c)] = \cdots \text{fill in} \cdots = 2F(c) - 1$

showing that minimum is obtained for $2F(c) - 1 = 0$, or $c = \text{median}(X)$

(End of proof)
Example 2  
Consider the simple case of $X$ being the result of throwing a fair die, with pmf,  

$$f(x) = P(X = x) = \frac{1}{6} \text{ for } x = 1, 2, \ldots, 6.$$  

An easy calculation gives us  

$$\mu = E(X) = 3.5$$  

which, according to crit. 1 should be the best prediction of $X_{obs}$. This is, of course, nonsense since 3.5 is not possible as an outcome. This, however, does not mean that criterion 1 itself is nonsense. Note that crit. 1 just says to minimize  

$$E[(X - c)^2] = \sum_{x=1}^{6} (x - c)^2 \cdot \frac{1}{6}$$  

when $c$ is one of the permitted values, 1, 2, \ldots, 6.

Similarly, crit. 2 says to choose $c$ among 1, 2, \ldots, 6, so that  

$$E|X - c| = \sum_{x=1}^{6} |x - c| \cdot \frac{1}{6}$$  

becomes as small as possible. Using, e.g., Excel we get the table

<table>
<thead>
<tr>
<th>$c$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[(X - c)^2]$</td>
<td>9.2</td>
<td>5.2</td>
<td>3.2</td>
<td>3.2</td>
<td>5.2</td>
<td>9.2</td>
</tr>
<tr>
<td>$E</td>
<td>X - c</td>
<td>$</td>
<td>2.5</td>
<td>1.8</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>$E[L_3(c)]$</td>
<td>5/6</td>
<td>5/6</td>
<td>5/6</td>
<td>5/6</td>
<td>5/6</td>
<td>5/6</td>
</tr>
</tbody>
</table>

Hence, both crit. 1 and crit. 2 lead to two equally good solutions for the best prediction, i.e., $c = 3$ or $c = 4$. Crit. 3 says that any of 1, 2, \ldots, 6 will do as best prediction.

In the continuous case, if, e.g., $X \sim N(169, 36)$, then both crit. 1 and 2 would lead to 169 as the best prediction of a future $X_{obs}$. Remember that the expectation and the median are equal in symmetric distributions.

If $X \sim \exp(\lambda = 0.5)$, we have that $E(X) = \frac{1}{\lambda} = 2$ and median($X$) = $\frac{\ln 2}{\lambda} = 1.39$, so that crit. 1 would lead to 2 and crit. 2 to 1.39 as the best prediction respectively of a future $X_{obs}$.

Example 3  
Suppose $(X, Y)$ is a pair of rv’s with joint pdf, $f(x, y)$, which is known. We want to predict $Y$ for a given chosen value of $X$, i.e., for $X = x$. The relevant distribution for $Y$ to use for the prediction is then clearly the conditional distribution of $Y$ given $X = x$, with pdf, $f(y| x) = f(x, y) / f_X(x)$. The best prediction is then, according to criterion 1, given by the expectation in this distribution, i.e., $E(Y | x)$. For example, using the distribution in Rice defined on page 75,

$$(X, Y) \sim f(x, y) = \begin{cases} 12 \left( x^2 + xy \right) & \text{for } 0 \leq x \leq 1, \ 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Suppose we want to predict $Y$ when $X$ has the value, $X = 0.75$. In the lecture (10 september) we derived the conditional pdf (valid for $0 \leq x \leq 1$):
\[ f(y \mid x) = \frac{x + y}{x + 0.5} \quad \text{for} \quad 0 \leq y \leq 1 \]

and the expectation, \( \mu(x) = E(Y \mid x) = \frac{x + 2/3}{2x + 1} \). Hence, the best (following crit. 1) prediction of \( Y \) is \( \mu(0.75) = E(Y \mid 0.75) = \frac{0.75 + 2/3}{1.5 + 1} = 0.567 \).

2 Case 2 – Prediction of \( X \) when the distribution of \( X \) is unknown

We want to predict \( X \) when the distribution with pdf \( f(x) \) and \( \mu = E(X) \) are unknown. We will use the most common criterion 1 for choosing our predictor. The task is, thus, to find the best prediction, \( \hat{X} \), of \( X \) based on,

**Criterion 1** Choose \( \hat{X} \) to minimize \( MSE = E[(X - \hat{X})^2] \).

If \( \mu \) were known, we would use \( \hat{X} = \mu \), of course. \( \mu \) being unknown, the natural thing to do is to estimate \( \mu \) as good as we can from available data and use the estimate, \( \hat{\mu}_{\text{obs}} \), as our prediction. It turns out that this intuitive procedure is the correct one based on crit. 1, as the following theoretical argument shows:

**Elaboration.** Suppose that the available data are observations of \( X_1, X_2, \ldots, X_n \), which we denote as the vector \( D = (X_1, X_2, \ldots, X_n) \). For simplicity we assume that the future \( X \) to be predicted is independent of \( D \), implying that the conditional pdf, \( f(x \mid x_1, x_2, \ldots, x_n) = f(x \mid d) = f(x) \) does not depend on \( d \).\(^1\) This implies further that \( E(X \mid d) = E(X) = \mu \).

Now, our task becomes to construct our predictor \( \hat{X} = h(D) \) as a function of \( D \) in the best way, i.e., such that \( MSE = E[(X - \hat{X})^2] = E[(X - h(D))^2] \) is minimized.

Applying the theorem of total expectation on the MSE, we get

\[
MSE = E[(X - h(D))^2] = E[E[(X - h(D))^2 \mid D]] = Eg(D)
\]

where \( g(d) \) is the function,

\[
g(d) = E[(X - h(D))^2 \mid D = d] = E[(X - h(d))^2 \mid D = d]
\]

\(^1\) This assumption is typically reasonable for cross section data where \( D \) often consists of iid variables. For time series data, however, where \( X_i \) represents the value of the series at time point \( i \), and \( X \) the value of the series at a future time point, there will often be dependence between \( X \) and \( D \). The conclusion of the argument, however, will still be the same, i.e., the best prediction of \( X \) will simply be the best estimate of \( E(X \mid d) \).
noting that \( h(d) \) is just a constant in the conditional distribution given \( D = d \). Now we can do the same thing as in the proof of \textit{crit.1} on page 2, adding and subtracting the expected value, \( E(X \mid d) \), inside \( (X - h(d))^2 \), and we get

\[
\begin{align*}
g(d) &= E[(X - E(X \mid d))^2 \mid D = d] + (E(X \mid d) - h(d))^2
\end{align*}
\]

As we saw above, \( E(X \mid d) = E(X) = \mu \), giving

\[
\begin{align*}
g(d) &= E[(X - \mu)^2 \mid D = d] + (\mu - h(d))^2
\end{align*}
\]

But, also \( (X - \mu)^2 \) is independent of \( D \), so we can drop the conditioning in the first term in \( g(d) \), giving

\[
\begin{align*}
g(d) &= E[(X - \mu)^2] + (\mu - h(d))^2 = \sigma^2 + (\mu - h(d))^2 , \text{ where } \sigma^2 = \text{var}(X) .
\end{align*}
\]

Now it only remains to replace \( d \) by the rv \( D \) in \( g(d) \) and take expectation to find

\[
\begin{align*}
\text{MSE} = Eg(D) &= E[\sigma^2 + (\mu - h(D))^2] = \sigma^2 + E[(\mu - h(D))^2].
\end{align*}
\]

From this result we can conclude

**Conclusion**

The best predictor, \( \hat{X} = h(D) \), according to \textit{crit.1} is a function of the data \( (D) \) that minimizes \( E[(\mu - h(D))^2] \), or, in other words, \( h(D) \) is the best estimator, \( \hat{\mu} = h(D) \), of \( \mu \), minimizing \( E[(\mu - \hat{\mu})^2] \).

This ends the theoretical elaboration confirming the intuition we started with, namely that the problem of predicting \( X \) reduces to the problem of estimating \( \mu = E(X) \).

This also tells us how to predict (using \textit{crit.1}) a response variable \( Y \) based on a given value, \( X = x \), of an explanatory variable, \( X \):

- If \( E(Y \mid x) \) is known, the best prediction of \( Y \) is given by \( E(Y \mid x) \).
- If \( E(Y \mid x) \) is unknown, the best prediction of \( Y \) is given by the best possible estimate, \( \hat{E}(Y \mid x) \), of \( E(Y \mid x) \).

For example, if \( E(Y \mid x) = \alpha + \beta x \), the best prediction of \( Y \), given \( X = x \), is \( \hat{Y} = \hat{\alpha} + \hat{\beta} x \), where \( \hat{\alpha} \), \( \hat{\beta} \) are good estimators, for example OLS in the case of homoscedasticity. This is the reason that Stata (and other packages) usually call the expression \( \hat{\alpha} + \hat{\beta} x \) for “predicted \( Y \”).

Note that, even if the prediction problem gives the same answer (estimate) as an estimation problem, it is wrong to look at the two problems as the same. The difference between
prediction and estimation does not appear in the estimates, but rather in the uncertainty. The uncertainty of a prediction (measured by a so called “prediction interval”) is larger than the uncertainty of the corresponding estimation (as measured by a confidence interval). This will be illustrated in the following example 4 with data.

Example 4
We will use the mother/daughter data collected from Stat 1 lectures (Econ2130) in the period 2010-2012. (The data, consisting of \( n = 125 \) observations, can be downloaded as an Excel-file from [http://folk.uio.no/haraldg/](http://folk.uio.no/haraldg/) under the heading Econ2130.) In addition to prediction we will also use the example as an opportunity to discuss the important iid model often used for cross section data.

Let \( X \) denote the height of the mother and \( Y \) the height of the daughter for a randomly chosen pair from the population. This we express by saying, \((X,Y) \sim f(x,y)\) where the pdf \( f(x,y) \) represents the population distribution.

The problem is to predict the height of the daughter (\( Y \)) for a particular pair where the mother has height, \( X = x_0 = 160 \). (It could, for example, be a case where the mother has only one child, a daughter who is just a small child, and we want to predict how tall the daughter will be when she grows up.)

We will use criterion 1 as our guide line for “best prediction”.

The first model assumption is that we have a representative sample from the population. More precisely:

1. The data are observations of an iid sample of random pairs, 
   \((X_1,Y_1),(X_2,Y_2),\ldots,(X_n,Y_n),\) where \((X_i,Y_i) \sim f(x_i,y_i)\) for \( i = 1,2,\ldots,n \).

Note that this implicitly implies representativity in the sense that the sample would have been non-representative if, e.g., the common distribution of \((X_i,Y_i)\) \( i = 1,2,\ldots,n \), were different from the population distribution \( f \).

There are strong reasons to postulate that the regression function for \( Y \) with respect to \( X \) (i.e., \( \mu(x) = E(Y \mid x) \)) is a linear function of \( x \) in this situation. (For example, assuming that \((X,Y)\) is bivariate normally distributed, which is an empirically well founded assumption for homogeneous height data, the linearity of the regression function is automatically fulfilled – even the assumption of homoscedasticity.) So we assume

2. Regression function: \( \mu(x) = E(Y \mid x) = \alpha + \beta x \), where \( \alpha, \beta \) are unknown constants.

3. Homoscedasticity: \( \sigma^2(x) = \text{var}(Y \mid x) = \sigma^2 \) - constant.

If \( \alpha, \beta \) were known, we would use \( \mu(x_0) = \mu(160) = \alpha + \beta x_0 = \alpha + \beta \cdot 160 \) as our best prediction. Since they are unknown, however, we will need to estimate them in order to obtain a prediction.
For the sample, from assumptions (1), (2), (3), it follows that for \( i = 1, 2, \ldots, n \),
\[
E(Y_i \mid x_i) = \mu(x_i) = \alpha + \beta x_i
\]
and \( \text{var}(Y_i \mid x_i) = \sigma^2 \). Notice here that \( x_i \) represents the observed value of the rv \( X_i \) and, as such, a fixed number. Introducing error terms, \( e_i = Y_i - \alpha - \beta x_i \), we can write this equivalently as \( Y_i = \alpha + \beta x_i + e_i \) for \( i = 1, 2, \ldots, n \), where \( E(e_i \mid x_i) = 0 \) and \( \text{var}(e_i \mid x_i) = \text{var}(Y_i - \alpha - \beta x_i \mid x_i) = \text{var}(Y_i \mid x_i) = \sigma^2 \) (using that \( \alpha + \beta x_i \) is a constant in the conditional distribution given \( X_i = x_i \)). Hence it appears that we can use the simple regression model presented in Stat 1 (Econ2130) where the values, \( x_1, x_2, \ldots, x_n \), of the explanatory variable are assumed to be fixed numbers.

That this is allowed will be justified theoretically in the appendix below. The fixation of the explanatory variable to the observed values is a highly convenient measure, simplifying the estimation problem considerably, and is used a lot in econometrics when dealing with exogenous explanatory variables. But, of course, it needs a theoretical justification…

Thus our model for the data is the same as in the Stat 1 course:

\[
Y_i = \alpha + \beta x_i + e_i \quad \text{for} \quad i = 1, 2, \ldots, n
\]

where the error terms \( e_1, e_2, \ldots, e_n \) are iid rv’s with \( e_i \sim N(0, \sigma^2) \), and where \( x_1, x_2, \ldots, x_n \) are fixed numbers.

Note that the normality of \( e_i \) follows automatically if \( (X_i, Y_i) \) is bivariate normally distributed (a reasonable assumption here) which implies that the conditional distributions are normal as well. So \( (e_i \mid x_i) \sim N\left(E(e_i \mid x_i), \text{var}(e_i \mid x_i)\right) = N(0, \sigma^2) \).

Note also that \( e_i \) is a non observable variable (also called a latent variable) since it depends on the unknown \( \alpha, \beta \). However, it can be estimated (i.e., predicted) by the predictor (called residual), \( \hat{e}_i = Y_i - \hat{\alpha} - \hat{\beta} x_i \) for \( i = 1, 2, \ldots, n \). In general, residuals contain important information when judging the realism of some model and is therefore often used as a diagnostic tool for this purpose.

Introducing the population parameters,
\[
\mu_X = E(X), \quad \mu_Y = E(Y), \quad \sigma_X^2 = \text{var}(X), \quad \sigma_Y^2 = \text{var}(Y), \quad \sigma_{XY} = \text{cov}(X, Y),
\]
these can be estimated by the sample analogues
\[
\bar{X}, \quad \bar{Y}, \quad S_X^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2, \quad S_Y^2 = \frac{1}{n-1} \sum_{i=1}^{n} (Y_i - \bar{Y})^2, \quad S_{XY}^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})
\]
respectively. (It can be proven that if \( (X, Y) \) is bivariate normal these will be equal to the maximum likelihood estimators except that \( 1/(n-1) \) in the variance/covariance formulae’s is replaced by \( 1/n \).)

Introducing the correlation between \( X \) and \( Y \), \( \rho = \sigma_{XY} / (\sigma_X \sigma_Y) \), this can be estimated by the sample analogue,
\[
r = S_Y / (S_X S_Y) \quad \text{(which will, actually, be equal to the mle estimator in bivariate normal case)}.
\]
Using model (4) we can replace all \( X_i \) by the observed values, \( x_i \), and consider \( \bar{x} \) and \( s_x^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \) as constants and \( S_{xy}^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})(Y_i - \bar{Y}) \). The OLS estimators are then given by \( \hat{\beta} = \frac{S_{xy}}{s_x^2} \), \( \hat{\alpha} = \bar{Y} - \hat{\beta}\bar{x} \), \( \hat{\mu}(x) = \hat{\alpha} + \hat{\beta}x \), and the regression variance,

\[ \sigma^2 = \text{var}(Y \mid x) = \sigma_y^2 (1 - \rho^2) \], is estimated by \( \hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^{n} e_i^2 = \frac{n-1}{n-2} \left( S_{y}^2 - \hat{\beta}^2 s_x^2 \right) \)

(see, e.g., the Stat 1 course for formulae’s). Estimates are given in the table

Table of estimates. (Sample size, \( n = 125 \))

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_X )</td>
<td>( \bar{x} )</td>
<td>166.9</td>
</tr>
<tr>
<td>( \mu_Y )</td>
<td>( \bar{y} )</td>
<td>167.6</td>
</tr>
<tr>
<td>( \sigma_X )</td>
<td>( s_x = \sqrt{s_x^2} )</td>
<td>5.8232</td>
</tr>
<tr>
<td>( \sigma_Y )</td>
<td>( s_y = \sqrt{s_y^2} )</td>
<td>5.5938</td>
</tr>
<tr>
<td>( \sigma_{XY} )</td>
<td>( s_{xy} )</td>
<td>11.7315</td>
</tr>
<tr>
<td>( \beta )</td>
<td>( \hat{\beta} = s_{xy} / s_x^2 )</td>
<td>0.346</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>( \hat{\alpha} = \bar{Y} - \hat{\beta}\bar{x} )</td>
<td>109.96</td>
</tr>
<tr>
<td>( \mu(160) )</td>
<td>( \hat{\mu}(160) = \hat{\alpha} + \hat{\beta} \cdot 160 )</td>
<td>165.3</td>
</tr>
</tbody>
</table>

According to this, our prediction of the daughter’s height when she grows up is 165.3.

Note that the estimate, \( \hat{\mu}(160)_{\text{obs}} = 165.3 \) now has two interpretations

- It is the (OLS) prediction of a single case of daughter’s height when the mother is 160 cm.
- It is the (OLS) estimate of the mean in the population of daughter’s heights with mothers all being 160 cm.

**Evaluation of uncertainty (in terms confidence/prediction intervals).**

95% confidence interval (CI) for \( \mu(x_0) = \mu(160) \):

According to results given in the Stat 1 course, \( T_i = \frac{\hat{\mu}(x_0) - \mu(x_0)}{\text{SE}(\hat{\mu}(x_0))} \overset{\text{exactly}}{\sim} t_{n-2} \) distributed (i.e., \( t \)-distribution with \( n-2 \) degrees of freedom). When \( n \) is so large as 125, the \( t_{123} \)-distribution is practically almost identical with the \( N(0,1) \) distribution, so we may as well state \( T_i \overset{}{\sim} N(0,1) \).

\( \hat{\mu}(x_0) = \hat{\alpha} + \hat{\beta}x_0 \) is unbiased and with variance

\[
\text{var}(\hat{\mu}(x_0)) = \sigma^2 \left( \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{(n-1)s_x^2} \right)
\]
The formulae for the (estimated) standard error is

\[ SE(\hat{\mu}(x_0)) = \hat{\sigma} \sqrt{\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{(n-1)s^2_x}} \]

where \( \hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^{n} \hat{e}^2_i = \frac{n-1}{n-2} \left( S^2_y - \hat{\beta}^2 s^2_x \right) \). Using \( T_i \sim N(0,1) \), we get

\[
0.95 = P(-1.96 \leq T_i \leq 1.96) = P\left(-1.96 \leq \frac{\hat{\mu}(x_0) - \mu(x_0)}{SE(\hat{\mu}(x_0))} \leq 1.96\right) =
\]

\[
P\left[ \hat{\mu}(x_0) - 1.96 \cdot SE(\hat{\mu}(x_0)) \leq \mu(x_0) \leq \hat{\mu}(x_0) + 1.96 \cdot SE(\hat{\mu}(x_0)) \right]
\]

Using \( x_0 = 160 \), the estimates become \( \hat{\sigma}_{obs}^2 = (5.2396)^2 \) and

\[
SE(\hat{\mu}(160))_{obs} = \hat{\sigma}_{obs} \sqrt{\frac{1}{n} + \frac{(160 - \bar{x})^2}{(n-1)s^2_x}} = \hat{\sigma}_{obs} \cdot (0.139) = 0.728 \text{ , giving}
\]

**A 95% CI for } \mu(160):

\[
[\hat{\mu}(160) \pm 1.96 \cdot SE(\hat{\mu}(160))]_{obs} = 165.3 \pm 1.96 \cdot 0.728 = [163.9, 166.7]
\]

**A 95% prediction interval (PI) for } Y \mid X = 160:

Instead of the standard error of \( \hat{\mu}(x_0) \), we now use the square root of mean squared error (MSE) of the predictor \( \hat{Y} = \hat{\mu}(x_0) \):

\[
MSE = E\left[ (Y - \hat{\mu}(x_0))^2 \mid X = x_0 \right] = E\left[ (Y - \mu(x_0) + \mu(x_0) - \hat{\mu}(x_0))^2 \mid X = x_0 \right] = \cdots =
\]

\[
= E\left[ (Y - \mu(x_0))^2 \mid x_0 \right] + E\left[ (\mu(x_0) - \hat{\mu}(x_0))^2 \right] = \text{var}(Y \mid x_0) + \text{var}(\hat{\mu}(x_0)) =
\]

\[
= \sigma^2 + \sigma^2 \left( \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{(n-1)s^2_x} \right) = \sigma^2 \left( 1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{(n-1)s^2_x} \right)
\]

Notice that we have gotten an addition to the variance of \( \hat{\mu}(x_0) \) that does not get smaller when \( n \) increases.

Let us call the estimated version of the square root of MSE for \( SE(\hat{Y}) \). Then

\[
SE(\hat{Y}) = \hat{\sigma} \sqrt{\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{(n-1)s^2_x}} \text{ with observed value, } SE(\hat{Y})_{obs} = 5.287
\]

Now, in the normal case (\( Y \) being normally distributed), it can be proven\(^2\) that

\(^2\) Technical details about the construction of \( t \)-distributed rv’s (as well as \( F \)-distributed rv’s) can be found in Rice chapter 6.
\[ T_2 = \frac{Y - \hat{\mu}(x_0)}{\text{SE}(\hat{Y})} \sim t_{n-2} \] - which we here can identify with the \( N(0,1) \) distribution. Hence, the

same calculation as above gives us

\[ 0.95 = P(-1.96 \leq T_2 \leq 1.96) = P\left( -1.96 \leq \frac{Y - \hat{\mu}(x_0)}{\text{SE}(\hat{Y})} \leq 1.96 \right) = \]

\[ = P\left( \hat{\mu}(x_0) - 1.96 \cdot \text{SE}(\hat{Y}) \leq Y \leq \hat{\mu}(x_0) + 1.96 \cdot \text{SE}(\hat{Y}) \right) \]

So the 95% “prediction interval” (PI) for \( Y \) becomes, \( \hat{\mu}(x_0) \pm 1.96 \cdot \text{SE}(\hat{Y}) \). The observed

value of the PI for \( x_0 = 160 \) is

\[ \left[ \hat{\mu}(160) \pm 1.96 \cdot \text{SE}(\hat{Y}) \right]_{\text{obs}} = [165.3 \pm 1.96 \cdot 5.287] = [154.9, 175.7] \]

which is considerably larger than the corresponding CI for \( \mu(160) \).

**Appendix**  
**Theoretical justification that the observed values of the explanatory variable can be considered as fixed numbers in the regression model**

The starting point is the iid model in (1) repeated here

\[ (8) \text{ The data are observations of an iid sample of random pairs,} \]

\[ (X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n), \text{ where } (X_i, Y_i) \sim f(x_i, y_i) \text{ for } i = 1, 2, \ldots, n. \]

where \( f \) represents the population distribution for \((X, Y)\). This implies that the joint pdf of all

the variables (denoted by \( \bar{f} \)) can be written\(^3\)

\[ (9) \quad \bar{f}(x_1, y_1, x_2, y_2, \ldots, x_n, y_n) = f(x_1, y_1) f(x_2, y_2) \cdots f(x_n, y_n) \]

\(^3\) The factorization actually uses a slightly more general concept of independence than given in the lecture. Namely that one group of rv’s is independent of another group of rv’s if the joint pdf of all variables is the product of the two marginal joint pdf’s for the two groups. For example, \((X_i, Y_i)\) and \((X_j, Y_j)\) are independent pairs if the joint pdf can be factotized, \( \bar{f}(x_i, y_i, x_j, y_j) = f_i(x_i, y_i) f_j(x_j, y_j) \), where \( f_i, f_j \) are the marginal joint pdf’s of the two pairs respectively obtained by integrating out the other variables from \( \bar{f} \). this implies (in the same way as in the lecture) that any event formulated in terms of the first pair ( e.g., \( X_i < Y_i \) ) is independent of any event formulated in terms of the second pair ( e.g., \( |X_i/Y_i| > 3 \) ). It also implies that \( X_i, X_j \) are independent as well as \( Y_i, Y_j \).
We can also factorize $f$ using the conditional distribution of the $Y_i$'s given all the $X_i = x_i$

\begin{equation}
\bar{f}(x_1, y_1, x_2, y_2, \ldots, x_n, y_n) = f(y_1, y_2, \ldots, y_n | x_1, x_2, \ldots, x_n) \cdot f_1(x_1, x_2, \ldots, x_n)
\end{equation}

where $f_1$ is the marginal joint pdf of all the $X_i$'s obtained by integrating out all the $y_i$'s from $\bar{f}$. If all the arguments, $x_i, y_i$'s are equal to the observed values of $X_i, Y_i$, (10) gives the likelihood function of our data with log likelihood

\begin{equation}
l(\theta) = \ln \bar{f} = \ln f(y_1, y_2, \ldots, y_n | x_1, x_2, \ldots, x_n) + \ln f_1(x_1, x_2, \ldots, x_n)
\end{equation}

where $\theta = (\alpha, \beta, \sigma^2, \theta_1, \ldots, \theta_r)$ is the vector of all the parameters in the model. We notice that, from the model formulation (4), that all the three parameters of interest, $\alpha, \beta, \sigma^2$, occur in the first term only in (11) and not in the second term, so that, when we develop the mle estimators for these parameters by derivation, the derivative of the second term ($\ln f_1$) will always be zero. In other words, the maximization of the full likelihood function with respect to the three parameters of interest, $\alpha, \beta, \sigma^2$, is equivalent to maximizing the conditional likelihood, $f(y_1, y_2, \ldots, y_n | x_1, x_2, \ldots, x_n)$ with respect to $\alpha, \beta, \sigma^2$. Hence we can consider the observations, $x_1, x_2, \ldots, x_n$, as given fixed numbers when estimating $\alpha, \beta, \sigma^2$.

This argument, referring to the maximum likelihood principle for estimating the parameters of interest, is the usual argument used in the econometric literature for justifying considering the observed values, $x_i$'s, as given fixed numbers in the model. It may also be mentioned that the fact that the parameters of interest do not occur in the marginal pdf $f_1$ sometimes is used as one (of several possible) statistical definitions of $X$ being exogenous.

In this situation we may simplify the conditional joint $f$ further. First notice that the model (8) implies that $X_1, X_2, \ldots, X_n$ are iid rv’s with pdf

\begin{equation}
f_2(x_1, x_2, \ldots, x_n) = f_2(x_1) f_2(x_2) \cdots f_2(x_n)
\end{equation}

where $f_2(x_i)$ is the (common) marginal pdf of $X_i$ for $i = 1, 2, \ldots, n$. Using (9)-(11) we get

\begin{equation}
f(y_1, y_2, \ldots, y_n | x_1, x_2, \ldots, x_n) = \frac{f_1(x_1, y_1, x_2, y_2, \ldots, x_n, y_n)}{f_1(x_1, x_2, \ldots, x_n)} = \frac{f(x_1, y_1) f_2(x_2) f_2(x_3) \cdots f_2(x_n) f(y_2, y_3) \cdots f(y_n) f(x_2) f_2(x_3) \cdots f_2(x_n)}{f_2(x_1) f_2(x_2) \cdots f_2(x_n)} = f(y_1 | x_1) f(y_2 | x_2) \cdots f(y_n | x_n)
\end{equation}

showing that, given all $X_i = x_i$ for $i = 1, 2, \ldots, n$, then $Y_1, Y_2, \ldots, Y_n$ are independent but with different pdf’s

\[ Y_i | x_1, x_2, \ldots, x_n \sim f(y_i | x_i) \]

or
\[ f(y_i \mid x_1, x_2, \ldots, x_n) = f(y_i \mid x_i) \]

which exactly represents the model given in (4) and shows that we can drop all \( x_j \)'s except \( x_i \) from the distribution of \( Y_i \) - which is actually due to the independence of \( X_1, X_2, \ldots, X_n \).

From this we may draw even further important conclusions. If \( \eta \) is one of the three parameters, \( \alpha, \beta, \) and \( \mu(x) = \alpha + \beta x \), the theory for the model gives that the OLS estimators satisfy

\[
T = \frac{\hat{\eta} - \eta}{\text{SE}(\hat{\eta})} \bigg|_{x_1, x_2, \ldots, x_n} \sim t_{n-2}
\]

which we use for inference about \( \eta \). Since the \( t_{n-2} \) distribution does not depend on \( x_1, x_2, \ldots, x_n \), we can conclude that \( T \) is even marginally (without the conditioning) \( t_{n-2} \) distributed\(^4\)! So confidence intervals and tests about \( \eta \), developed under the fixed values assumption for \( X_1, X_2, \ldots, X_n \), is still valid without the conditioning.

However, the distribution of \( \hat{\eta} \) itself may depend on the conditioning. For example, from the theory of model (4), the OLS estimator \( \hat{\beta} \) satisfies (writing \( \bar{x} \) for \( x_1, x_2, \ldots, x_n \)),

\[
(14) \quad \hat{\beta} \mid \bar{x} \sim N \left( \beta, \var(\beta \mid \bar{x}) \right) = N \left( \beta, \frac{\sigma^2}{(n-1)S^2_x} \right)
\]

implying that the marginal distribution of \( \hat{\beta} \) no longer is normal. On the other hand, (14) implies that

\[
E(\hat{\beta} \mid \bar{x}) = \beta \quad \text{(i.e., a constant function of } \bar{x})
\]

so the theorem of total expectation gives

\[
E(\hat{\beta}) = E \left[ E(\hat{\beta} \mid \bar{x}) \right] = E(\beta) = \beta
\]

\( \hat{\beta} \) is therefore still unbiased! However, the variance becomes complicated

\[
\var(\hat{\beta}) = E \left[ \var(\hat{\beta} \mid X) \right] + \var \left[ E(\hat{\beta} \mid X) \right] = E \left[ \frac{\sigma^2}{(n-1)S^2_x} \right] + \var[\beta] = \frac{\sigma^2}{(n-1)} \left[ \frac{1}{S^2_x} \right]
\]

which is complicated.

\(^4\) Remember from the lectures that if \( (U, V) \sim f(u, v) \), and the conditional pdf, \( f(v \mid u) \) does not depend on \( u \), then \( U \) and \( V \) must be independent and \( f(v \mid u) = f_j(v) \), i.e., the marginal pdf of \( V \). This is true (why?) even if \( U \) consists of several variables.